Topological properties of ride-pooling shareability graph as a proxy to key performance indicators

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SHORT SUMMARY

Ride-pooling is a promising and actively developing branch of urban mobility. Algorithmic solutions match travellers with feasible rides using a so-called shareability graphs. However, analysis in the field present very little information on the topological structure of such graphs. In the paper, we experiment with varying demand levels and behavioural parameters of travellers sharing rides in Delft, Netherlands, to observe changes in the graph structure and see how properties of the graph correlate with ride-pooling KPIs. We observed strong relations in our experimental study, suggesting that there is potential to use Network Science tools in order to better understand shareability in the ride-pooling problem.

Keywords: Network science, Ride-pooling, Shareability

1. INTRODUCTION

Transportation network companies (often referred as to TNCs) such as Uber, Lyft and Didi offer ride-pooling services. Wide body of literature shows that such services are beneficial in terms of transportation efficacy, infrastructure, and environment (Shaheen et al., 2016). In the paper, we use exact matching algorithm ExMAS proposed by Kucharski and Cats (2020) which relies on a utility criterion. Travellers are matched into a shared ride if the ride satisfies timing requirements (like e.g. in Alonso-Mora et al. (2017)) but also if it is attractive for each traveller. Performance of ride-pooling systems across the various system settings are reported by Kucharski and Cats (2020), Tachet et al. (2017), or Santi et al. (2014). One of the central methods to analyse pooling is the so-called shareability graph (Santi et al., 2014), which can be expressed in a form of bipartite graph where nodes are on one side travellers and on other rides, linked if a traveller belongs to that particular pooled ride.

In the paper, we exploit the topological properties of such graphs. We present experimental evidence that there is a high correlation between input parameters, topological properties of shareability graph and key performance indicators (KPIs) of the ride pooling. We apply the structural characteristics such as *square clustering coefficient* (Lind et al. (2005)), node degree and cover of a giant component, which are not only highly correlated with inputs and KPIs, but also have a direct network science interpretation.

2. METHODOLOGY

Creating shareability graph with ExMAS

ExMAS is an offline algorithm which matches the travellers into a shared ride if it satisfies timing requirement (i.e. time window between requests and pick-up delay) and is more attractive than a single ride for all the passengers. More precisely, travellers are assigned to the shared rides if individual utility of the shared ride exceeds a utility value of non-shared ride for each of the co-assigned travellers. Value of the utility depends strongly on the individual- and system-dependent variables with the following formula, given as the difference between shared ride and non-shared ride:

$$U = U^s - U^{ns} = \beta^c \lambda l + \beta^t (t - \beta^s (\hat{t} + \beta^d \hat{t}^p)) + \varepsilon, \tag{1}$$

where U, U^s, U^{ns} denote respectively utility gain due to sharing, utility of shared ride and utility of non-shared ride. λ stands for discount for sharing a ride and is controlled by the system operator. β^c, β^t, β^d are the behavioural parameters: cost sensitivity, sharing discomfort and delay sensitivity. t and $\hat{t}$ stand for travel time by non-shared and shared ride respectively. $\hat{t}^p$ is a pick-up delay, the difference between pick-up times for non-shared and shared ride. Here we assume deterministic formulation (the random term ε is constant 0). We will say that shared ride is attractive if $U \geq 0$. Based on the aforementioned criteria, ExMAS yields shareability graph. It is a bipartite graph comprising travellers and attractive rides. The most simple part of the graph is single rides. It consists of a set of pairs that connect single traveller with a single (non-shared) ride. The rest of the graph corresponds to shareable rides. Two (or more) travellers are assigned to a ride if the ride is attractive for each of them. Only attractive shared rides form a graph.

ExMAS produces several ride-pooling performance indicators, from which the most meaningful indicators are: utility change (which stands for benefit from user perspective); saved vehicle hours (important from the operator, sustainability the and congestion perspective) and the ratio of shared rides within the final matching.

Shareability graph properties

In the experiments (detailed in the next section) we have inspected several structural properties of the graph. In the Table 1, we present the part of the correlation matrix corresponding to the relationship between graph properties and KPIs of the final matching. Based on this findings we selected the promising network measures to further investigate their relation with ride-pooling shareability.

Table 1: Correlation between structural properties of the shareability graph and KPIs of the final matching.

	Shared rides	**Saved vehicle hours**	**(Dis)Utility gain**
Degree	0.906	0.960	-0.963
Degree rides	0.913	0.963	-0.959
Degree travellers	0.555	0.665	-0.682
Clustering rides	0.856	0.905	-0.926
Clustering travellers	0.880	0.931	-0.966
Clustering shared rides	0.855	0.870	-0.865
Clustering shared travellers	0.487	0.523	-0.552
Greatest component	0.944	0.905	-0.856
Shareable travellers	0.974	0.925	-0.860

Degree denotes average degree in the graph, while degree rides/travellers stands for an average degree within nodes belonging to respective groups. Standard clustering coefficient is based on triangles, which by definition do not exist in the bipartite graph (Lind et al., 2005). Hence, we calculated square clustering coefficient with the formula given by Zhang et al. (2008) which is currently implemented in *NetworkX* (version 2.6.3). In pursuit of better understanding of shareability, we have removed single rides from the graph. Then, we calculated what we called *clustering shared rides/travellers* on such subgraph. We also calculated the relative size of the greatest component (the biggest fraction of nodes that are connected). The last structural parameter is denoted by *shareable travellers*. It accounts for a fraction of traveller nodes that are connected to at least one shared ride. What we denote by *(dis)utility* stands for the utility penalty. Hence, we aim to reduce the utility.

Even though the average degree highly correlates with the ride-pooling KPIs, we dismissed it as a good proxy, since it was hardly interpretable. Degree of rides corresponds strictly to the number of passengers assigned to it. Naturally, it is highly correlated with KPIs, however; it yields little information about the graph structure. We have concluded that the two most significant structural properties are clustering travellers and shareable travellers. Square clustering coefficient calculated for traveller nodes presents a probability that for any two rides connected to a traveller, there is a second traveller with whom both rides can be shared. Shareable travellers stand for the fraction of travellers who can share some ride. We were also interested in how input parameters impact size of the greatest component and average degree of traveller node. First is a good measure showing graph's connectivity while the second gives an information about robustness and reliability of pooling. Degree of a traveller is in fact the number of rides that he/she can be assigned to.

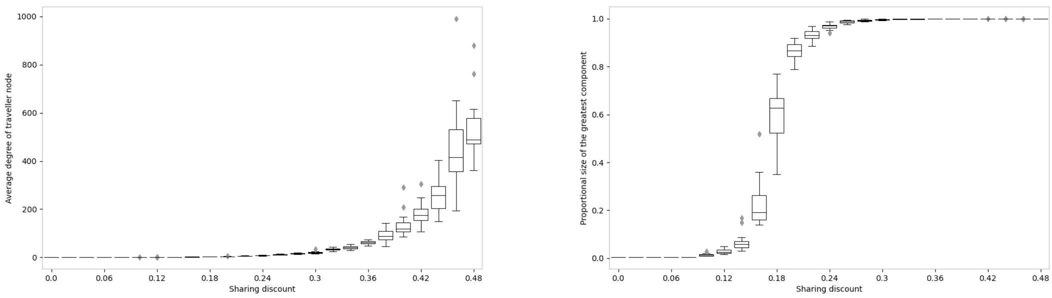
3. RESULTS AND DISCUSSION

We conducted the experiment for medium-size city Delft in Netherlands. We obtained the city map from OpenStreetMap using OSMnx (Boeing, 2017) and computed a skim matrix. Next, we sampled demand with the given number of trips. For graph analysis, we used another freely accessible Python library NetworkX (Hagberg et al., 2008). Simulation time was one hour. To get reliable results, we performed experiments with different system settings 10 replications for each set of settings. It is important to note that for each replication at given number of trips; we generated different demand (different origins, destination, time of requests).

Primary findings, correlation matrix (Table 1), figures 3 and 4 are calculated for varying share discount level (λ of eq.1) from 0.1 to 0.4 with 0.02 steps and number of travellers (demand level) from 150 to 300 by 50. For further insight, we have fixed number of rides to 250 and broaden share discount interval, so it ranged from 0 to 0.48 (figures 1 and 2). Similarly, we fixed the discount factor λ to 0.26 and increased number of rides up to 500.

Impact of share discount λ on graph properties

We have found that share discount has a tremendous impact on the structural properties of the shareability graph. In the Figure 1 we observe how it affects the average degree of traveller node and relative size of the greatest component. The results are computed for a fixed number of trips at level of 250. Shape of plot 1a resembles exponential growth. Share discount approaching 0.5 results in shareability scheme where average traveller is being assigned to several hundreds of rides. On one hand, we can say that graph is robust and system should be resistant to small perturbations (such as removing some rides). However, we must point out that it comes at high computational cost, as it requires finding optimal matching within huge number of rides. In the plot 1b, we observe a phase transition of the relative size of the greatest component. Starting from no discount, there are no shareable rides, as each is less attractive than a single ride. Hence, the greatest component is just a single pair (meaning that a traveller is connected with a ride, not that of two travellers joining the same ride). Around λ =0.08, we observe how shareable rides appear. Then, there is a quick growth of the greatest component. Usually, the graph becomes connected for share discount of around 0.3.



(a) Degree travellers

(b) Greatest component

Figure 1: Impact of share discount λ on the two properties of bipartite shareability graph. On the left-hand side, we observe a dynamic increase of average degree of traveller node around 0.3. Average number of rides assigned to a single traveller reaches as high as one thousand in some replications with share discount approaching 0.5. On the right-hand side, we can see the phase transition. Spare graph structure for discount values less than 0.1 transitions into the connected graph, which is nearly always the case for discount of 0.3 and above.

We have concluded that the two important structural graph parameters, which can be used as a proxy to KPIs of the final matching, are average clustering coefficient of traveller node and a fraction of travellers who can share a ride. In the Figure 2, we show how those parameters are affected by a change in the discount factor λ. Confidence intervals are narrow, which suggests that there is a little deviation with respect to replications. It is particularly visible with the percentage of travellers who can share. Once again, we see coefficients equal to zero as long as there are no shared rides. First shared rides appear at around 0.08. It is followed by a rapid growth of percentage of travellers who can share a ride. Already at discount 0.2 it reaches around 80%. Then it converges to 100% usually reaching it at 0.3 discount. Average value of square clustering coefficient grows slower than the percentage of potentially sharing travellers. We can observe that the growth decelerates at around 0.4.

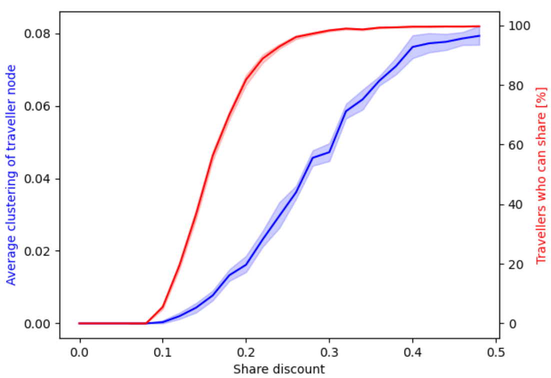


Figure 2: Average clustering of traveller node and fraction of travellers that are connected to a shared rides as a function of the shared discount λ. We can observe that both coefficients are around 0 when share discount is not greater than 0.1. Then we see a rapid growth of travellers who can share and milder growth of clustering coefficient. Fraction of travellers who can share converges to 1 around a discount factor of 0.3.

Structural properties of shareability graph against system KPIs

We have found that structural properties of bipartite shareability graph are highly correlated with system's key performance indicators. In the Figure 3, we present results with varying both number of rides and shared discount.

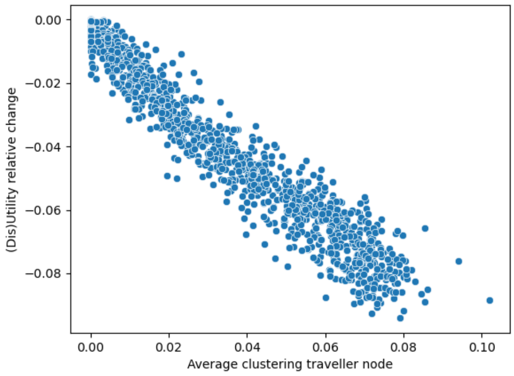


Figure 3: Relation between average clustering coefficient of a traveller node and a relative change in the utility for ride-pooling. We can see that the values seem to be (negatively) correlated.

We can see that relative change in utility seems to proportionally decrease with an increase of average clustering of traveller node. If we think of square clustering coefficient for traveller node as of flexibility in the system, it makes sense that higher coefficient benefits in utility. Looking at the pattern of the plot, we can see that there is, in fact, little deviation. Regardless of the huge number of input settings, there is an strong relation. We can see that, in some extreme cases, the clustering coefficient is equal or close to zero, while there is a benefit in terms of utility. It usually occurs when in the final matching there are nearly none rides of degree three and higher. Indeed, if in shareability graph, each of the ride nodes was of degree no higher than two, square clustering coefficient of traveller nodes would equal zero.

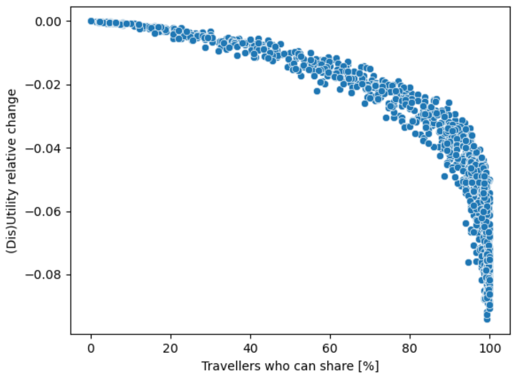


Figure 4: Relation between average clustering coefficient of traveller node and relative change in the utility of the final matching. We can see that the values seem to be (negatively) proportional.

Figure presents the relationship between the fraction of potentially sharing travellers and utility. It turns out that as long as there are at least 40% of isolated travellers who can choose only a single ride (no more than 60% travellers who can share), the gain in utility is lesser than 2%. We can see that utility gain at the level of at least 6% is possible if there are at least 90% of travellers who can share. The system allows only a portion of non-shareable travellers to be effective. It is important to note that in the graph, we see even the extreme case when the number of rides was as low as 150. It means that very similar law governs even when the density of requested trips is low.

4. CONCLUSIONS

Demonstrated empirical evidence indicates that effectiveness of ride-pooling highly correlates with topological properties of shareability graph - which is a novel findings that shall be further exploited in the filed of ride-pooling. We provide insight into the relationship between inputs, structural characteristics of the graph and key performance indicators of the final matching. We examined several graph structural measures and identified the ones well explaining shareability, we identified phase transitions of ride-pooling critical mass, we identified two regimes of ride-pooling (first when ride-pooling becomes feasible and second when it becomes stable) and explain them with two separate network measures. In the future studies, for more solid conclusions, those findings shall be explored on the bigger networks, real-world demand levels and spatial patterns.

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